

# A NOVEL METHOD FOR MRI BRAIN IMAGE SEGMENTATION

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**Abstract:** This paper presents an automatic segmentation algorithm for MRI (magnetic resonance imaging brain image). The algorithm integrates morphological Algorithm and histogram-based fuzzy Cmeans (FCM) to segment brain into three major classes of gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF). First, morphological is used to Removal of extracranial tissues to get brain image and then histogram-based FCM algorithm is used to segment the images. The algorithm was implemented in MATLAB code. Satisfied results were obtained.

**Key-Words-** segmentation, image, brain, mri, morphology, histogram-based fuzzy Cmeans

## I. INTRODUCTION

When working with medical images it is often of interest to delineate interesting areas or volumes. The process of finding those is called segmentation. Magnetic resonance images (MRI) of human brain typically contain three tissue classes: gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF), as shown in Figure (1).

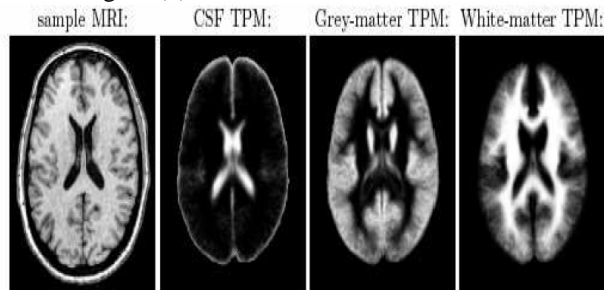


Fig.1 three tissue classes: gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF)

Fully automatic, accurate and robust brain tissue classification from these MRI data is of great importance for research and clinical studies of the normal and diseased human brain. Segmentation methods for performing tissue classification are mainly hindered by the following three imaging artifacts. First, because the intensities of MR images are sensitive to the conditions or imaging parameters of the scanners, we don't have a clear-cut correspondences between the intensities and the biological tissues. There may be big overlaps of the intensity distribution ranges among different tissues. Second, the second difficult is the inhomogeneities of

the magnetic field and biological variations in different structures belonging to the same tissue class. Third, the last main problem is the partial volume effects in MR images which made the tissue boundary blurred [1]. Because of these, using conventional intensity-based method to classify MR images is problematic. In the paper, we proposed an algorithm not only taking use of the characteristic of the intensity distribution but also the morphological character

## II The MORPHOLOGICAL METHOD

1) *Background on mathematical morphology:* Image morphology provides a way to incorporate neighborhood and distance information into algorithms (see Serra, 1982; Haralick et al., 1987 for detailed treatment of morphological operators). The basic idea in mathematical morphology is to convolve an image with a given mask (known as the structuring element) and to binarize the result of the convolution using a given function. Choice of convolution mask and binarization function depend on the particular morphological operator being used. Binary morphology has been used in several segmentation systems.

- **Erosion:** an erosion operation on an image  $I$  containing labels 0 and 1, with a structuring element  $S$ , changes the value of pixel  $i$  in  $I$  from 1 to 0, if the result of convolving  $S$  with  $I$ , centered at  $i$ , is less than some predetermined value. We have set this value to be the area of  $S$ , which is basically the number of pixels that are 1 in the structuring element itself. The structuring element (also known as the erosion kernel) determines the details of how a particular erosion thins boundaries.
- **Dilation:** dual to erosion, a dilation operation on an image  $I$  containing labels 0 and 1, with a structuring element  $S$ , changes the value of pixel  $i$  in  $I$  from 0 to 1, if the result of convolving  $S$  with  $I$ , centered at  $i$ , is more than some predetermined value. We have set this value to be zero. The structuring element (also known as the dilation kernel) determines the details of how a particular dilation grows boundaries in an image.
- **Conditional dilation:** a conditional dilation is a dilation operation with the added condition that only pixels that are 1 in a second binary image,  $I_c$ , (the image on which the dilation is conditioned), will be changed to 1 by the dilation process. It is equivalent to masking the results of the dilation by the image  $I_c$ .

- Opening: an opening operation consists of an erosion followed by a dilation with the same structuring element.
- Closing: a closing operation consists of a dilation followed by an erosion with the same structuring element.[2]

### 2) Removal of extracranial tissues to get brain image:

An important pre-processing step is the removal of extracranial tissues because our segmentation technique labels the entire brain into three classes: gray matter (GM), white matter(WM) and cerebrospinal(CFS). In the paper, morphological method were used to remove extracranial tissue. The results for one MRI image shown in Figure. 2.

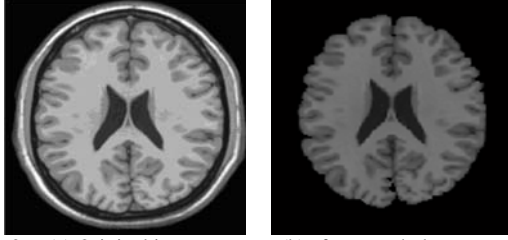


Fig.2 . (a) Original image (b) after morphology

### III.The Fuzzy C-means Method

use of fuzzy segmentations over hard segmentations in defining anatomical structures. Fuzzy segmentations retain more information from the original image than hard segmentations by taking into account the possibility that more than one tissue class may be present in a single voxel and has previously been used with some success in the fuzzy segmentation of magnetic resonance (MR) as well as for the estimation of partial volume [3].It clusters data by computing a measure of membership ,called the fuzzy membership, at each voxel for a specified number of classes. The fuzzy membership function, constrained to between zero and one, reflects the degree of similarity between the data value at that location and prototypical data value or centroid, of its class. Thus, a high membership value near unity signifies that data value at that location is "close " to the centroid for that particular class.

1) *Histogram-based FCM algorithm*:Histogram-based FCM method was used in the paper for segment the brain,which only use the I-D histogram and thus can greatly simplify the segmentation computation. The algorithm based on the principle that for a gray level only belongs to two neighbor parts with different membership, and the nearer with the centroid of that part, the higher membership it has, thus greatly simplify the fuzzy segmentation computation. We get good segmentation results by optimizing the objective function of fuzzy Restrained FCM clustering. Although FCM algorithm is robust to initial centroid, proper selection will generally improve accuracy and convergence of the algorithm. In order to closely and easily estimate the initial centroids,we developed a weighted histogram with very similar peak and vale property and smoother than the original histogram.

2) *Initial Centroids*: In order to properly select the initial centroid values, a weighted histogram PH (k) (including the background ) was constructed by using gaussian

function as smoothed kernel estimator of image histogram (see equation 1) and used to estimate the three peaks as the initial centroid values estimation  $v_j$  ,  $k=1,2,3$ , for WM,GM and CSF.

$$P_H(K) = \frac{1}{P_{MAX}} \sum_{g=0}^{255} H(g) e^{\frac{-(g-k)^2}{4}} \quad (1)$$

$$P_{MAX} = \max(P_H(g))$$

3) *The procedure to find the three peaks is as followings*:

1 : find the gray level corresponding the maximum peak of weighted histogram.

2. find the second large peak: a simple trick that frequently works well enough is to look for the second peak by multiplying the histogram value by the square of the distance from the first peak. This gives the preference to peaks that are not close to the maximum. So, if the largest peak is at level  $j$  in the weighted histogram, select the second peak as[4]:

$$\max\{((k-j)^2 P_H(k)) | (0 \leq k \leq 255)\} \quad (2)$$

In the same way, we can find the gray level corresponding to third largest peak. Sort order the three gray levels by ascending, we get the corresponding centroid values.Figure.3

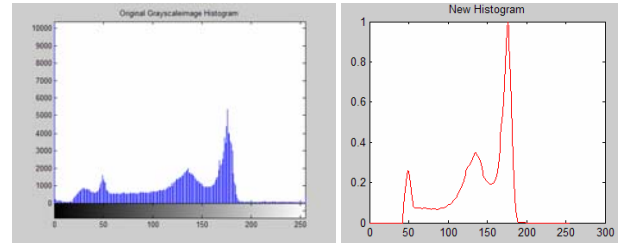


Fig.3.(a) Original grayscale image histogram (b)Weighted histogram

Develop the Restrained Histogram Fuzzy Membership Function:

$$W_{ik} = \begin{cases} \frac{k - v_1}{v_2 - v_1} & v_1 \leq k \leq v_2 \\ \frac{k - v_2}{v_3 - v_2} & v_2 \leq k \leq v_3 \\ 1 & 0 \leq k \leq v_1 \\ or & v_3 \leq k \leq 255 \\ 0 & Otherwise \end{cases} \quad (3)$$

K : the gray level of the image  
i : the classes to be segmented

Compute the objective function JHFCM of histogram based FCM method.

$$J_{HFCM} = \sum_{k=0}^{255} \sum_{i=1}^3 u_{ik}^m w_{ik} \|k - v_i\|^2 H(k) \quad (4)$$

By minimizing the objective function, we get the

Optimized  $u_{ik}$  and  $v_i$ .

$$u_{ik} = \frac{[w_{ik} / (k - v_i)^2]^{1/(m-1)}}{\sum_{p=1}^3 [w_{pk} / (k - v_p)^2]^{1/(m-1)}}$$

$$v_i = \frac{\sum_{k=0}^{255} (u_{ik}^m . k . H(k))}{\sum_{k=0}^{255} (u_{ik}^m . H(k))} \quad i = 1, 2, 3 \quad (5)$$

$U = [u_{ik}]_{3 \times 256}$  fuzzy histogram clustering division matrix

$V = [v_i]_{1 \times 3}$  the centroids matrix of different tissues in brain

Properly selecting weighting exponent m is also important for producing good cluster in FCM algorithm. Figure.4

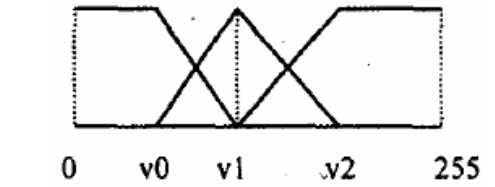
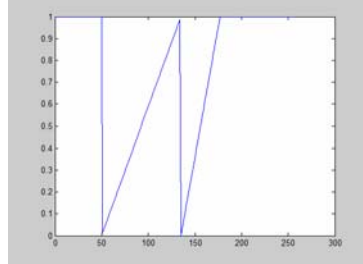


Fig.4.a) Restrained histogram fuzzy membership function



b) fuzzy membership function of image

Though there is no theoretic methodology, experiment results demonstrate its effectiveness and arrive at the conclusion that the optimal selected range m is [1.5 2.5]. In the paper, we use m=1.75

$$\|V^{(n)} - V^{(n-1)}\| \leq \epsilon \quad n \text{ ..iterative times}$$

,then using potential function as height readjustment function to modulate the clustering division matrix and get optimized thresholds for segmenting image based on maximum cluster rule.

$$F_i(k) = p_H(v_i)U_i(k)$$

$$T_i = x_i, \quad F_i(x_i) = F_{i+1}(x_i) \quad i = 1, 2 \quad (6)$$

we use this method to segment brain( image(a) in figure 2)and get the threshold  $T_1 = 25$ (for CSF , CSF and the background are in the same class but our algorithm segmented CSF from the background , therefor it is no necessary to classify them) ,  $T_2 = 112$  and  $T_3 = 146$ . results is shown in Figure.5.



Fig.5.Results of our segmentation

#### IV. Conclusion

This paper described an MRI brain image segmentation algorithm which works in two steps: morphological method and histogram-based fuzzy C-means (FCM) for segmenting the brain image into three tissues GM, WM and CSF. Satisfied results were obtained.

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